Testing different methods of incorporating climate data into the assessment of US West Coast sablefish

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The objective of this investigation was to evaluate different methods of including environmental variability directly into stock assessments and to demonstrate how this inclusion affects the estimation of recruitment parameters, stock status, and the conservation benchmarks used to manage a stock. Variations on two methods of incorporating environmental effects were tested. The first method ("model" method) utilizes a structural change in the stock–recruitment function to adjust the annual expected number of recruits by a value, either positive or negative, equal to that year's anomaly in the environmental variable. The second method ("data" method) allows for observation error in the environmental data and uses the time-series as an index to tune the vector of estimates of annual recruitment deviations. Simulation techniques were utilized to produce datasets of known quantities that were subsequently analysed with a widely used stock assessment platform. Under the circumstances simulated in this study, neither method could be said to have performed significantly better than the other in all situations. Because the two approaches handle years of missing data differently, the best approach is dictated by the available data, rather than a more appropriate method.

Keywords: climate, environmental covariates, parameter estimation, stock assessment.

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Introduction

It has long been accepted that environmental factors play a major role in accounting for year-to-year variability in exploited fish stocks (Hjort, 1914; Cushing, 1982). These environmental factors can include changes in air and ocean temperatures (Chavez *et al*., 2003), upwelling (Ware and McFarlane, 1995), or timing of the spring transition (Logerwell *et al*., 2003). One of the main ways that the environment influences fish population dynamics is by modulating annual recruitment, usually in the form of young of the year survival. Explicitly including environmental variables underlying this modulation into stock assessments can help determine whether changes in recruitment are a result of changes internal (i.e. parental stock size or spawning–stock biomass) or external (i.e. changes in recruit survivorship) to the population structure. At least three situations can benefit from the inclusion of environmental data: (i) environmental variability causes a large deviations in recruitment, but conventional fishery and survey data are not adequate to capture this variability clearly, so including environmental data helps the model estimate the correct time-series of recruitment; (ii) fish recruit to the fishery at a young age, but there are no surveys of young fish to estimate the recent levels of recruitment; (iii) there is a long-term signal in the environment that affects recruitment, but this trend is confounded with a one-way decrement in the spawning biomass. In this regard, including environmental data can decrease the variance in parameter estimation and help to determine the true stock–recruitment relationship and subsequent management benchmarks.

The standard approach to include environmental data into population models has been through the addition of a parameter to the standard stock–recruitment function, which allows recruit survival to deviate annually from the mean levels predicted by the simpler function (Hilborn and Walters, 1992, p. 285). Because this approach modifies the structure of the existing stock–recruitment model by adding a parameter, this method is referred to here as the model method. The shortcoming of the model method is that it relies on the unrealistic assumption that the environmental index is measured without error. Furthermore, because this method accounts for the portion of the overall recruitment standard deviation caused by the environment through the additional parameter in the modified stock–recruitment function, the environmentally caused deviation no longer contributes to the overall recruitment standard deviation, usually an assumed (i.e. not estimated) value in the stock assessment model. This necessitates that the assumed overall recruitment standard deviation value be reduced to reflect variation attributable only to forces other than the environment. However, because the level of the overall recruitment standard deviation scales the log-bias adjustment (so that the expected arithmetic mean recruitment is equal to the mean from the stock–recruitment function), this reduced value causes an incorrect log-bias adjustment for the estimates of both the annual as well as the virgin recruitment values.

Another approach that seeks to overcome the shortcoming of the model method is to use the environmental time-series in the same manner that an age-0 survey is used. With this approach, the environmental data are considered an index of recruitment variability and, as such, are used to tune the time-series of annual recruitment deviations from the fitted stock–recruitment curve (Brandon *et al.*, 2007). Because the environmental time-series is fitted as part of the stock-assessment-model objective function, and hence contributes to the total maximum likelihood component, this approach is referred to as the data method. Similar to a survey, the data method allows the environmental data to have annual observation error associated with it and, unlike with the model method, missing years are treated only as missing years of data. The environmental effect is assumed to occur after any density-dependence on recruitment has taken effect.

It has been demonstrated that recruitment of the US west coast sablefish (*Anoplopoma fimbria*) is influenced by changes in the environment (Schirripa and Colbert, 2006). Attempts to model this influence were made in the most recent sablefish stock assessment (Schirripa, 2007). The objective was to use simulation techniques to test the efficacy of the model and data methods and to determine the accuracy and precision of each. Simulation techniques were used to create a population of fish whose recruitment was modulated by a known environmental effect; then to assess the population using the two methods and to compare the estimated productivity values and management benchmarks with the true values, in an effort to discover whether any biases and/or inaccuracies were associated with each of the two methods.

Methods

An age-structured population model (FSIM) described in Goodyear (1989) was used to create the simulated datasets. Its application in the context of testing estimation methods has been demonstrated in several studies (Goodyear, 1996, 2007; Prager *et al.*, 1996; Prager and Goodyear, 2001). A simple fishery system was simulated, consisting of a single gear with data available annually on total catch, as well as samples of the age and length composition of the catch, and a single survey that provided estimates of annual stock biomass, as well as samples of age and length compositions. A variable was added to simulate cyclical variability in survival from egg to recruitment associated with temporal variations in the environment. The simulation model was implemented monthly based on female abundance only and it included environmental effects on the mean survivorship of age-0 recruits.

Simulated population data were fitted using the Stock Synthesis II (SS2) stock assessment framework (Methot, 2009). This framework uses a statistical catch-at-age approach to create a population time-series that best fits the given observations using maximum likelihood as the fitting objective. Details are given in Methot (2009). The SS2 model was given the true parameter values as the initial starting values with which to begin its iterative search for the set of maximum likelihood parameter estimates. The resulting estimates of parameter values and management benchmarks were compared with known values from the FSIM simulations.

Biological characteristics

The life-history characteristics described in the most recent sablefish stock assessment (Schirripa, 2007) were used to characterize the species. These included mass-at-length, growth, and fecundity functions. A natural (instantaneous) mortality rate of 0.07 was used in all simulations. Total mature female body mass was used as a proxy for the contributions to the spawning–stock biomass.

Annual recruitment in the simulated populations was determined from population fecundity at the beginning of each year, using a Beverton–Holt stock–recruitment function:

$$R = \frac{1}{\alpha + \beta/P},$$

where α is the rate of population growth, β controls the overall population size, and p the parental stock size. The stock–recruitment relationship controls mean recruitment for any given adult stock size. Mean recruitment at maximum sustainable yield (MSY) was set to 8000 fish; however, this number is arbitrary and had no effect on our results. Annual stochastic variability was added to the recruitment time-series by specifying a value for the coefficient of variation of recruitment greater than zero. This was accomplished by multiplying the predicted (mean) recruitment from the stock–recruitment relationship by $\exp(R \times CV - 0.5 \times CV^2)$, where R is a random normal deviate, with mean of zero and a variance of 1.0, and CV is the coefficient of variation of the log of the random multiplier.

When an environmental effect was desired, a long-term temporal trend was incorporated into the simulations by creating a time-series of deviations from mean recruit survival. These were incorporated into the simulation by multiplying the predicted (mean) recruitment from the stock–recruitment relationship by $\exp(D)$, where D is the assumed deviation from the expected recruitment in log units [i.e. $D = \log(O/E)$, where O is the "observed" recruitment and E the expected recruitment]. The 50-year time-series of observations of annual sea surface height off the coasts of Washington and Oregon was used as the environmental driver (Schirripa, 2007). Adding the sea surface height data resulted in an average recruitment deviation (σ_{Env}) of 0.6883, to which an additional random deviation (σ_{Rand}) of 0.4765 was added. This resulted in a total recruitment deviation (σ_{Total}) of 0.8371 given by,

$$\sigma_{\mathrm{Total}} = \sqrt{\sigma_{\mathrm{Env}}^2 + \sigma_{\mathrm{Rand}}^2}.$$

All simulated environmental observations were randomly drawn from a normal distribution with a mean equal to the observations and a coefficient of variation of 20% (Figure 1).

Simulations

The initial year of each simulation was designated 1951, and began with the population at its unfished stable age distribution, determined by M and the stock–recruitment curve. The population was then simulated through 2000, for a total of 50 years.

A particular fishery was simulated, starting 2 years after the start of the model, with asymptotic selectivity that operated only in June. The simulated fishery selectivity was length-based and followed a simple logistic function. The SS2 model was configured to length-based selectivity, and it utilized a two-parameter logistic model (i.e. assumed asymptotic). In all, 500 lengths and ages were sampled each year. Fishing mortality was set to $F = 0.14$, which is twice the natural mortality, $M = 0.07$.

Two simulated abundance indices were constructed for each simulated dataset. The first was from a simulated bottom-trawl

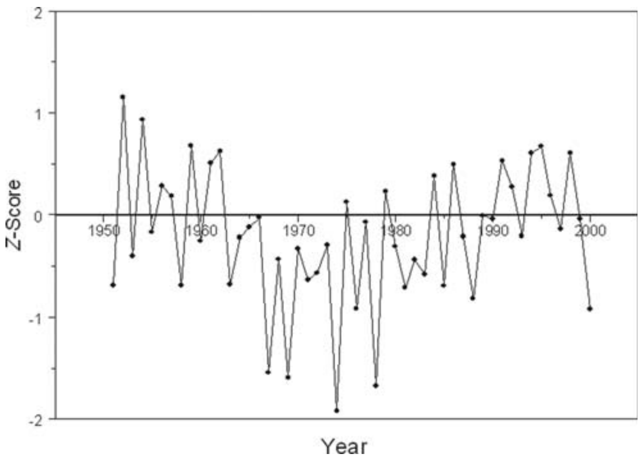

Figure 1. Spring sea surface height anomalies off the continental US west coast used as environmental time-series.

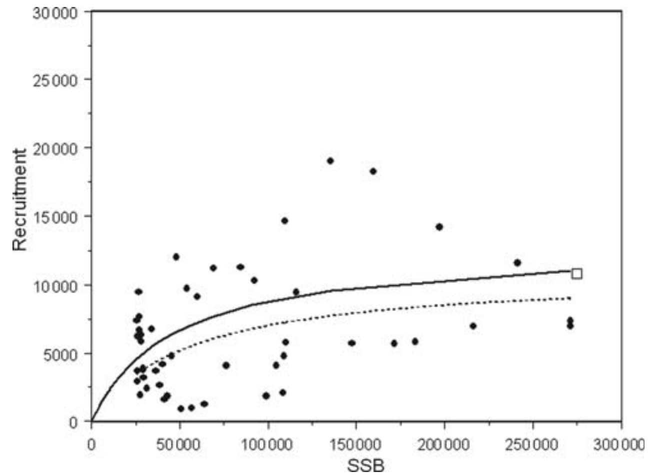

Figure 2. Typical Beverton–Holt stock–recruitment relation used for simulation. The dotted line represents the bias-corrected relationship.

survey, typical of those used on the US west coast for groundfish. This survey was simulated to have asymptotic, length-based selectivity, to operate only in July, and to have a *CV* of 0.20. In all, 500 lengths and ages were sampled each year. The second abundance index was constructed from the simulated environmental data. Annual estimates of simulated sea surface height were output with a *CV* of 0.20.

Model fitting

The expected abundance index *I* is related to the available population abundance by

$$L_{tf} = q_f B_{tf} \varepsilon_{tf},$$

where q_f is the catchability coefficient for fishery of survey *f* and ε_{tf} the abundance index error, assumed to be lognormally distributed as

$$\ln(\varepsilon_{tf}) \sim \mathrm{N}(-0.5\,\sigma_{tf}^2, \sigma_{tf}^2).$$

In the case where the environmental time-series was treated as data, B_{tf} was replaced with D_{tf}, which represents the recruit deviation for that year (see below).

Selectivity (S) for both the fishery and the survey was made length-based and followed the logistic equation

$$S = \frac{1}{1 + \exp(-\log(19)(L - \beta_1)/\beta_2)},$$

where L is the total length, β_1 the length at 50% selectivity, and β_2 the rate of increase to the asymptote. The SS2 model used a Beverton–Holt type stock–recruitment: relationship

$$\hat{R}_t = \frac{4hR_0S_t}{S_0(1-h) + S_t(5h-1)},$$

where R_t is the estimate of absolute recruitment in year *y*, *h* the parameter for steepness of the stock–recruitment function (where the value of *h* specifies the ratio of R_t to R_0 when $S_t = 0.2 \times S_0$; thus, the parameter *h* is bounded by 0.2 and 1.0), R_0 and S_0 the unfished equilibrium recruitment and spawning–stock biomass, respectively, and S_t the spawning–stock size in year *y* (Figure 2).

The model method directly adjusts the level of recruitment expected from the stock–recruitment function as

$$\hat{R}_t = f(\mathrm{SSB}_t) \times \exp(\beta E_t),$$

where β is the parameter relating the environmental time-series (E_t) to the recruitment deviation. For years where recruitment residuals were estimated, the level of total recruitment was given by

$$R_t = \hat{R}_t \exp(-0.5\sigma_R^2)\exp(\tilde{R}_t),$$

where σ_R is the standard deviation for recruitment in log space, and $\tilde{R}_t$ is the lognormal recruit deviation in year *y*. In our simulations, however, the value of σ_R that represents the total variation in recruitment was 0.8371, because the model method accounts for the environmental portion of the deviation within the stock–recruitment model structure itself. This value was reduced to 0.4764, so that it reflected only the random (i.e. non-environmental) portion of the total deviation.

The data method treats the environmental data as if it were a survey of annual recruitment deviations. This approach is similar to using the environmental index as if it were a survey of age-0 recruitment abundance. By focusing on the fit to the deviations, it removes the effect of spawning biomass on recruitment. In this method, the likelihood of the deviations are expressed as

$$\text{Likelihood} = 0.5\sum_t \left(\frac{\ln(E_t) - \ln(\hat{D}_t)}{\sigma_t}\right)^2,$$

where E_t is the environmental observation at time *t*, D_t the deviation from the fitted stock–recruitment function at time *t*, and σ_t the standard deviation of the observation error of the environmental time-series.

The calculation of deterministic, equilibrium MSY combines the yield-per-recruit and spawning biomass-per-recruit calculations with the recruitment levels calculated from the model's spawner–recruitment curve. The SS2 model searches for the fishing intensity multiplier that maximizes the product of yield-per-recruit and recruitment. The search algorithm is simple; it reverses direction and halves the search step each time the current calculation is less than the previous calculation for a fixed number of steps. With the Beverton–Holt spawner–recruitment curve, the equilibrium values are calculated from

$$S_{\mathrm{msy}} = a\frac{S'_{f\mathrm{msy}}}{R_0} - b, \text{ and}$$

$$R_{\mathrm{msy}} = \frac{4hR_0S_{\mathrm{msy}}}{S_0(1-h) + S_{\mathrm{msy}}(5h-1)},$$

where $S'_{f\mathrm{msy}}$ is the equilibrium spawning output with fishing intensity, *f*msy,

$$a = \frac{(4hR_0)}{(5h-1)},$$

$$b = \frac{S_0(1-h)}{(5h-1)}.$$

The SS2 model consisted of 83 parameters, of which 61 were freely estimated in the fitting process. These included three growth parameters, two stock–recruitment parameters, two survey catchabilities, four selectivity parameters, and recruitment deviations from 1951 to 2000. The total likelihood function included terms for indices of abundance, length and age compositions, size-at-age, and recruitment deviations.

Seven different simulation schemes were employed:

(i) Scheme 0: no environmental effect and no fitting method. This was used to establish baseline values against which to compare subsequent runs. The true values, with which the resulting distributions from this set of runs were compared, were corrected so that the central tendencies fell as close to zero as possible. All subsequent parameter estimate distributions were compared with these new corrected values. The time-series of recruitment estimates were not corrected in any manner.

(ii) Scheme 1: same as scheme 0, except output simulated data starting in 1990 (rather than 1951). All subsequent simulation start the data output in 1990 as well.

(iii) Scheme 2: introduce environmental effect into FSIM with no attempt to model it within SS2.

(iv) Scheme 3: maintain environmental effect in FSIM and use model method with no R_1 parameter (see below) within SS2 (explicit deviations from the S/R curve, assuming no measurement error).

(v) Scheme 4: maintain environmental effect in FSIM and use model method with estimated R_1 parameter within SS2 (the R_1 parameter is an exponential offset to the estimated R_0, which should calibrate for the reduced σ_R inherent in this method).

(vi) Scheme 5: maintain environmental effect in FSIM and use data method within SS2 (use environmental data as an age-0 survey with a $CV = 0.20$).

(vii) Scheme 6: maintain environmental effect in FSIM and use data method within SS2; allow the value of the σ_R parameter to be estimated within the assessment model (but does not contribute to the likelihood value).

The responses of the following variables were examined: unfished recruitment level (R_0), steepness of the stock–recruitment function (h), survey catchability (q), and MSY using percentage relative error: percentage relative error $= 100 \times [(\text{est} - \text{true})/\text{true}]$, where est is equal to the SS2 estimated value and true the adjusted value from the FSIM simulator.

Results

Properties of simulations

The degree of correlation between the percentage errors of the estimated parameters was similar between the various schemes. Therefore, correlations were calculated on the estimates aggregated between all the schemes (Table 1). Estimates of MSY were most strongly correlated with the estimates of h ($r = 0.52$), and least correlated with the estimates of catchability q ($r = -0.23$). Estimates of R_0 were most strongly correlated with estimates of MSY ($r = 0.37$) and least correlated with estimates of catchability q ($r = 0.06$).

To achieve a more accurate calibration between the simulation and assessment models, a set of 1000 simulations was run, which sampled 5000 ages and lengths from the simulated fishery and survey for all years (1951–2000). The true value of the simulated parameters was adjusted so that the central tendency of the percentage error of the resulting parameter estimate density plots was centred as close to zero as possible (see scheme 0 above).

When provided with large sample sizes from high-quality datasets from the FSIM simulator, the SS2 assessment model produced parameter estimates with a high degree of agreement with the true values from the simulator. However, minor adjustments to the true simulated values were necessary to centre the central tendencies of the resulting percentage-error density distributions exactly on zero. The required corrections were made to the following FSIM parameters: $R_0 = 0.6\%$; $h = 0\%$; $q = -4.0\%$, $\mathrm{MSY} = -5.0\%$. These adjustments were necessary because of slight differences in the manner that the two platforms handled such aspects as within-year growth and size- vs. age-at-first-maturity.

With the above-mentioned adjustments made, the SS2 model was able to fit all the parameters well when considering scheme 0. Estimates of the annual values of recruitment and spawning–stock biomass were also estimated with a great deal of accuracy and precision. This was partly attributable to the large amount of quality data available to fit the model. There were some slight differences in the central tendency of the density plots, which were adjusted for, to make subsequent differences more intuitive and easier to spot. These minor differences are believed to stem from the different assumptions between FSIM and SS2 with

Table 1. Pearson correlation coefficient matrix of the percentage error of the selected estimated parameters for all schemes.

	R_0	h	q	MSY
R_0	1.00			
h	−0.23	1.00		
q	0.06	−0.43	1.00	
MSY	0.37	0.52	−0.29	1.00

regard to growth. However, they did not significantly affect the final evaluations of the accuracy and precision of the various schemes considered in the study.

Shortening the data time-series resulted in estimates of the unfished recruitment level parameter (R_0) being overestimated (Figure 3, scheme 1). However, adding the environmental effect to the simulations accentuated the overestimation (Figure 3, scheme 2). The R_0 parameter was most accurately estimated when using the data method along with estimating σ_R within the assessment model (Figure 3, scheme 6). Although schemes 3–5 each improved the estimate of the R_0 parameter, the value was overestimated in each case, resulting in a risk-prone outcome (Table 2). This was likely because the environmental time-series started with mostly positive anomalies for the first 12 years (years 1951–1962; Figure 1). Coupled with this is the fact that there were fewer datapoints at higher levels of spawning–stock biomass. Therefore, that part of the stock–recruitment curve (and consequently the R_0 parameter) was estimated from fewer data points that were associated positive residuals.

Estimates of the steepness parameter (h) were more accurate than those of the R_0 parameter for all simulation schemes, although generally less precise (Figure 4). The addition of the environmental data added precision to the estimate of the h parameter. The most accurate estimate of h came from using scheme 2, whereas the least accurate estimate resulted from using scheme 5 (Table 2). The reason for this outcome is not obvious; however, a larger number of datapoints were in the portion of the stock–recruitment curve that has a greater influence on the estimate of steepness, this being the area of lower spawning–stock biomass (Figure 2). It is likely that the estimates of steepness are robust to whichever scheme is used for reasons similar to why the estimates of R_0 are

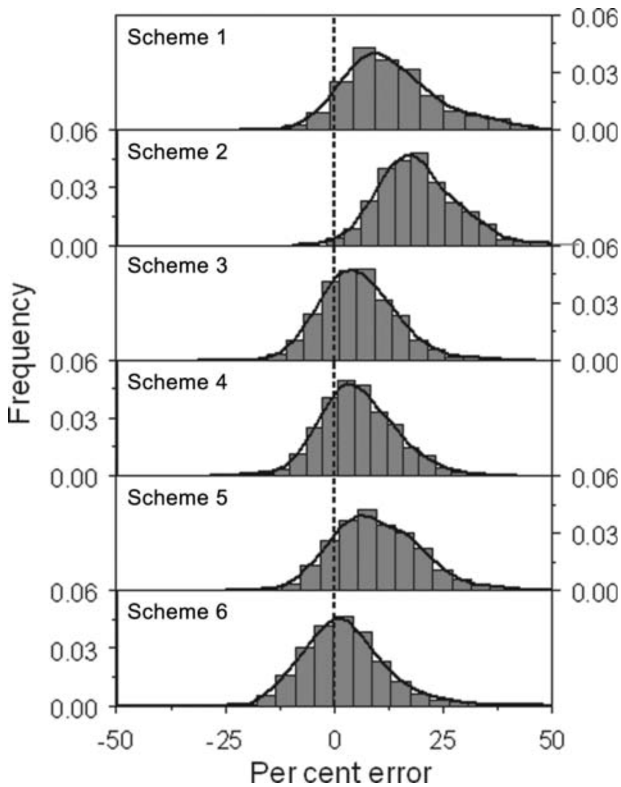

Figure 3. Density plots of percentage error for the estimates of the virgin recruitment (R_0) parameter across schemes.

Table 2. Mean, median, s.e., and lower (LCL) and upper (UCL) 95% confidence limits of each of the relative percentage errors for the estimated parameters under consideration.

	R_0	h	q	MSY
Scheme 1				
Mean	13.40	1.81	−3.86	14.37
Median	11.52	−0.69	−4.25	12.65
s.e.	0.35	0.48	0.50	0.80
LCL mean	12.70	0.87	−4.85	12.79
UCL mean	14.09	2.77	−2.87	15.94
Scheme 2				
Mean	19.24	−0.65	1.41	17.29
Median	18.50	−1.07	0.92	17.69
s.e.	0.28	0.21	0.48	0.54
LCL mean	18.70	−1.05	0.47	16.23
UCL mean	19.79	−0.24	2.35	18.35
Scheme 3				
Mean	5.47	2.17	−4.18	7.06
Median	5.06	1.12	−3.72	6.92
s.e.	0.26	0.29	0.46	0.48
LCL mean	4.95	1.60	−5.08	6.13
UCL mean	5.99	2.74	−3.28	8.00
Scheme 4				
Mean	5.50	2.12	−4.04	6.61
Median	4.91	0.77	−4.30	6.84
s.e.	0.27	0.29	0.48	0.54
LCL mean	4.97	1.55	−4.99	5.53
UCL mean	6.03	2.70	−3.10	7.69
Scheme 5				
Mean	9.75	8.61	−4.93	18.35
Median	8.91	7.10	−5.52	18.61
s.e.	0.31	0.36	0.59	0.69
LCL mean	9.13	7.91	−6.08	17.00
UCL mean	10.37	9.31	−3.78	19.70
Scheme 6				
Mean	2.31	−3.70	−2.00	−3.42
Median	1.59	−4.88	−2.04	−3.14
s.e.	0.29	0.32	0.60	0.48
LCL mean	1.74	−4.33	−3.18	−4.36
UCL mean	2.88	−3.08	−0.83	−2.47

less robust (i.e. the distribution of the simulated observations of spawning–stock biomass and recruits). Scheme 5 resulted in a slightly risk-prone estimate of h, whereas the scheme 6 estimate was more risk-averse.

Although the survey catchability parameter (q) was always underestimated by ~4%, compared with the other parameter estimates it was the most stable between schemes; however, it was also estimated with the least precision (Table 2, Figure 5). With the true catchability set at 1.0, the estimated catchability was estimated as ~0.96, which is well within the limits expected from an actual stock assessment estimate. Though not demonstrated or discussed here, estimates of q were also affected by the estimates of the selectivity parameters. The estimates of the two selectivity parameters were also very consistent between schemes and consistently slightly underestimated.

Relative to the other parameters, the estimates of MSY displayed considerably more variability between schemes (Table 2). When the environmental data were added, the estimates became more precise, but less accurate (Figure 6, scheme 2). Estimates of MSY were most accurate using scheme 6. All schemes resulted in a risk-prone estimate of MSY, except for scheme 6, which was slightly risk-averse.

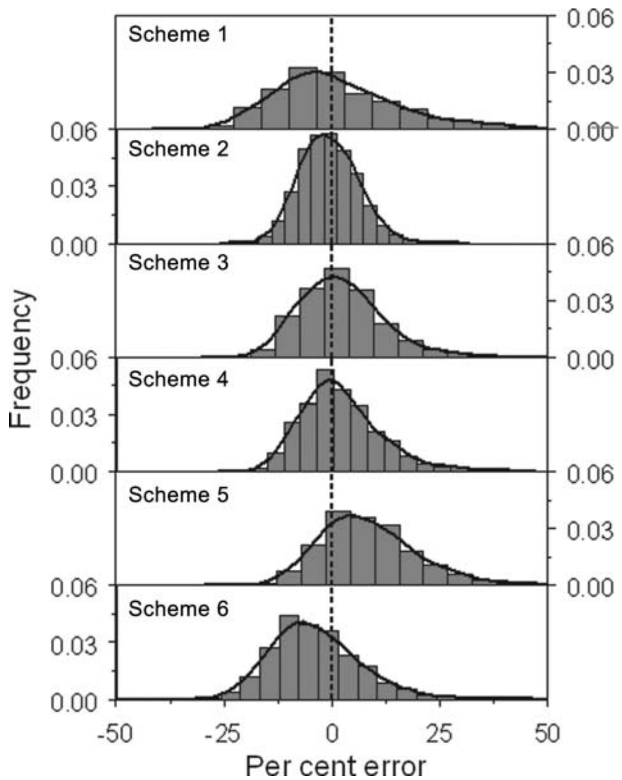

Figure 4. Density plots of percentage error for the estimates of the stock–recruitment steepness (h) parameter across schemes.

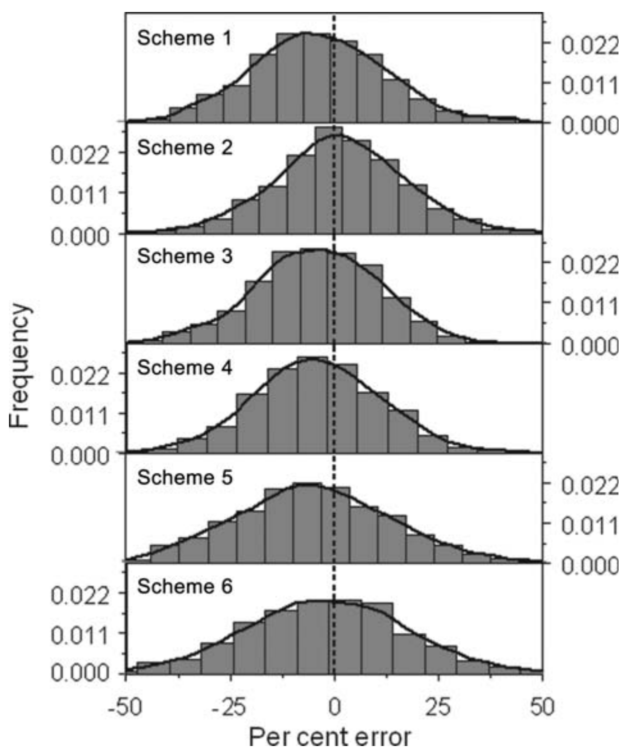

Figure 5. Density plots of percentage error for the estimates of the survey catchability (q) parameter across schemes.

The major effect of removing the first 40 years of data was to overestimate the R_0 parameter by 13.40% (Table 2). However, the steepness and survey q parameters were well estimated, being

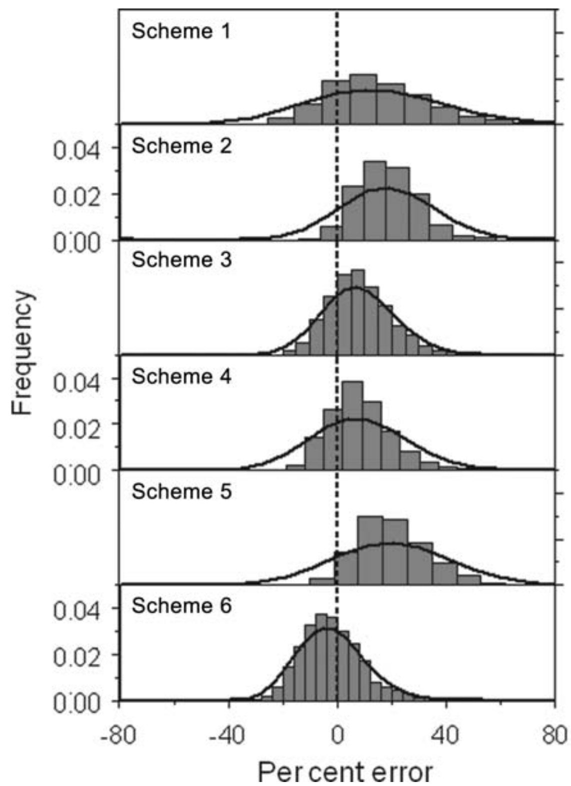

Figure 6. Density plots of percentage error for the estimates of MSY across schemes.

within 1.82 and −3.86% of the true values, respectively. The overestimation of R_0 resulted in an overestimate of MSY of 14.37%.

When the environmental signal was included in the simulations, with no explicit modelling for it, the estimates of R_0 were overestimated by 19.24% and steepness by only −0.65%. This in turn led to MSY being overestimated by ~17.29%. The q parameter remained well estimated. The environmental signal caused a great deal of imprecision in the estimates of annual recruitment. However, no bias was evident (Figure 7). Any apparent patterns in Figure 7 may be artifacts of the particular environmental time-series used and could have been different if a random point in the 50-year time-series were used to start the simulation. The residual pattern in recruitment resulted in a similar pattern in the spawning–stock biomass residuals (Figure 8).

Examination of the percentage error summed across all years indicates that recruitment was estimated more accurately than spawning–stock biomass (Figure 9). Spawning–stock biomass was consistently underestimated with the addition of the environmental signal, regardless of the scheme used. Scheme 3 resulted in not only the most accurate estimates of recruitment and spawning–stock biomass, but also the most precise (Figure 9). Scheme 6 resulted in least accurate estimates of both recruitment and spawning–stock biomass, as well as the least precise.

Discussion

Regardless of which scheme was used, the inclusion of the true environmental data resulted in better estimates of historical stock size and productivity than not including it. Although not included in this study, both methods could offer ways to determine whether the inclusion of the environmental data significantly improves the overall model fit. For the model method, if the

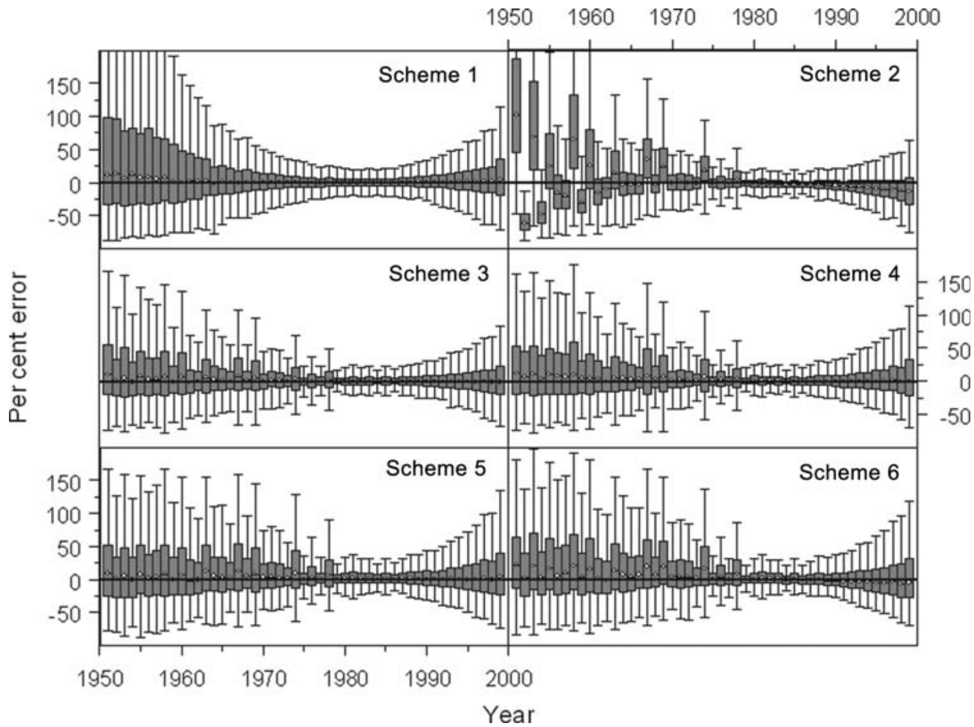

Figure 7. Error bars for percentage error of annual estimates of recruitment across all schemes.

addition of the β parameter reduces the total negative log likelihood by more than about two units, the additional parameter significantly improves the fit to the data at the 0.05 level, and there is a statistically significant correlation between the population process and the environmental time-series (Maunder and Watters, 2003). Although the data method assumes *a priori* that a relationship exists between recruitment and the environment, if the estimated standard deviation of the environmental time-series is much greater than the observed standard deviation, the time-series did very little, if anything, to improve the overall model fit.

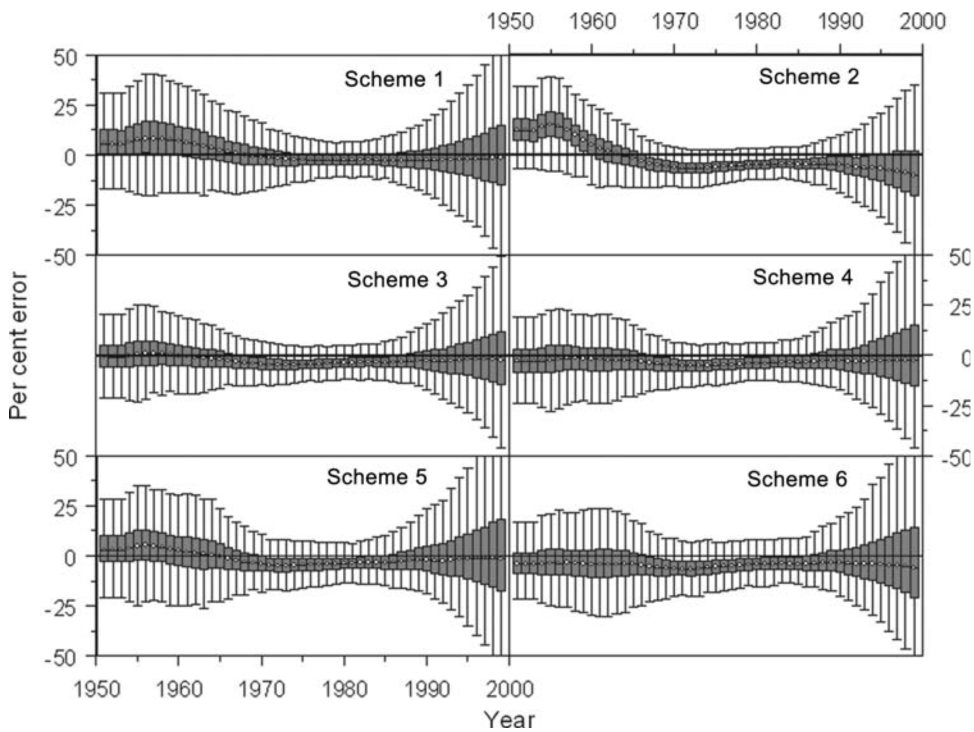

Figure 8. Error bars for percentage error of annual estimates of spawning–stock biomass across all schemes.

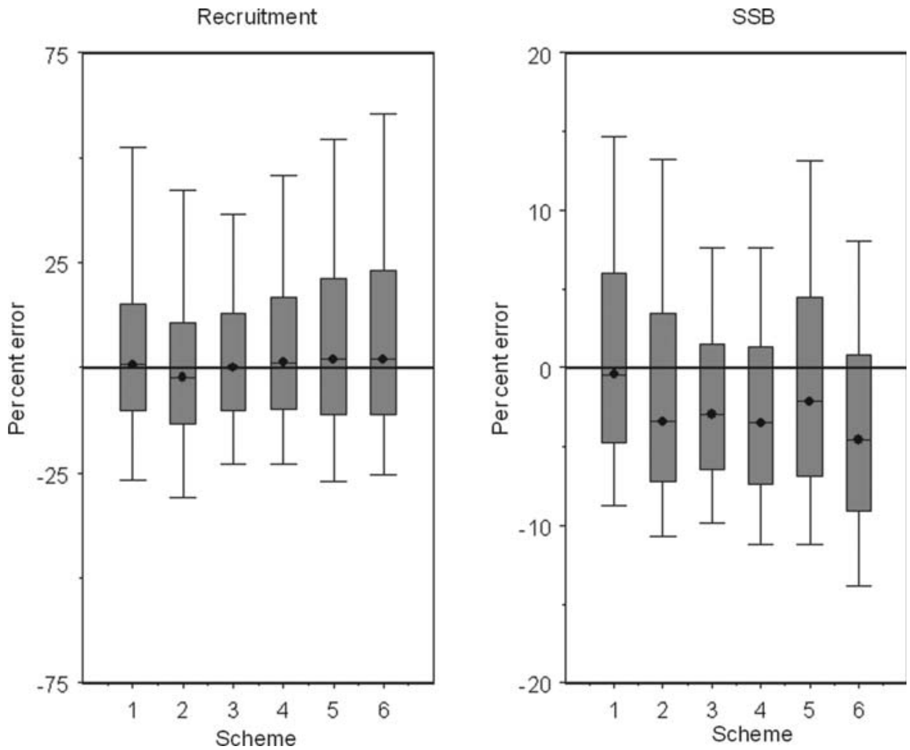

Figure 9. Error bars for the percentage error estimates across all schemes.

Including environmental data could be especially useful when faced with assessments of data-poor species. For instance, if the population dynamics of a data-rich representative species in a particular species assemblage can be demonstrated to respond to particular environmental covariates, assessments of data-poor species in that same assemblage could be done using the same environmental covariates. An example of such a situation was demonstrated for winter-spawning rockfish and changes in the winter sea level in the California Current system. Ten species of rockfish (*Sebastes* spp.) were demonstrated to have similar declining trends in recruitment from 1983 to 1998. All exhibited similar negative responses to *El Niño* conditions in 1983, 1992, and 1998, and all had similar recovery periods from 1999 to 2002 (S. Ralston, pers. com.). Environmental or climate data can also be incorporated into forecasts of possible future stock conditions. This can be especially useful if it is assumed that future climate conditions will exhibit a discernible trend. Either of the two methods discussed in this paper could be used to link climate forecast to future trends in recruitment. However, only the data method forces a likelihood compromise between recruitment values predicted directly from the stock–recruitment curve and those predicted by the environmental data index.

Under the circumstances simulated in this study, scheme 6 resulted in the most accurate estimations of the selected parameters. Scheme 6 also resulted in the greatest overall percentage error in the estimation of spawning–stock biomass; however, this error was only $\sim$5%. Overall, the performance of the model and the data methods was sufficiently similar to make it difficult to conclude that one was superior to the other. Because the model method used a reduced σ_R, the R_0 parameter had been expected to be more overestimated than was observed. This is one of the justifications for using the data method to avoid having to calculate the reduction in the σ_R value in the assessment model. One conclusion is that the signal in the simulated data was strong enough to arrive at an appropriate estimate of the virgin recruitment parameter (i.e. R_0). Despite these results, there are circumstances where the data method could be preferable to the model method. An example is when the environmental data are incomplete or contain years with no data. Short of some type of interpolation, years that contain no data would necessarily have a value of zero, which will be interpreted as a valid datapoint, representing no deviation for that year (i.e. average environmental conditions). The data method, on the other hand, would merely skip years with no data and allow the respective recruitment deviation to be fit to the remaining observation data sources. The data method may be the better choice if the stock assessment model does not have to estimate annual recruitment deviations. Furthermore, because the data method seeks to optimize the fit between both the fitted stock–recruitment function and the environmental index, it may be the preferred method for projecting possible future recruitment based on environmental forecasts. In this regard, the best modelling approach would be dictated by the available data, rather than the model.

This study was designed to simulate the particular biology and assessment of sablefish off the Pacific west coast of the continental United States, an eastern boundary current upwelling system. As such, the results may be associated with the particular annual patterns of the sea-surface-height index of this system and might not be fully applicable to other situations. Because the environmental time-series started with years with positive anomalies, the R_0 parameter was overestimated. Had the initial anomalies been negative, it is likely that the R_0 parameter would have been underestimated. For this reason, the year chosen from which to start the environmental time-series is critical and must be considered when interpreting the results. This first-year effect could have been investigated by starting each of the 1000 simulations at a random point within the environmental time-series. However, this study was initiated by interest in the actual sablefish assessment methodology. The first-year effect becomes more prevalent as the time-series shortens and the first year approaches the final year of the assessment. Consequently, the best approach might be to start the environmental time-series and the fitting of the assessment model as far back in time as the data permit, so allowing the parameters to be fitted using the widest range of variation possible. However, this approach implicitly assumes that an underlying environmental relationship actually existed for the earlier years within the model.

To arrive at a universal recommendation about which scheme is the best one required, a more extensive study that includes various annual environmental patterns is needed. This was beyond the scope of this paper. It is likely that, even with a more extensive examination of environmental patterns, one particular scheme might not be accepted as the best choice for all situations. For this reason, it is concluded that to find the best scheme for a particular assessment problem, a set of simulations similar to those outlined here should be conducted, using the actual datasets being considered within that particular assessment problem. Nonetheless, it is quite possible that the climatological and oceanographic processes indexed by sea surface height could index the productivity of the California Current system in general and hence modulate other important biological process. These biological processes, in turn, could modulate recruitment success directly or indirectly in other commercially important species in this ecosystem.

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